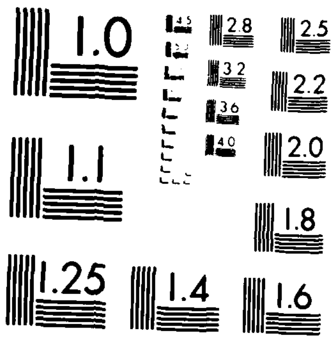
AD-A152 519 APPLICATION OF ARTIFICIAL INTELLIGENCE (AI) TO RADAR IMAGE UNDERSTANDING..(U) SOFTWARE ACCHITECTURE AND ENGINEERING INC ARLINGTON VA D T FRANKS ET AL. 1/1

UNCLASSIFIED 28 FEB 85 SAE-DC-85-R-004 ETL-0387 F/G 6/4 NL

END

FILMED

DTIC



MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

ETL-0387

AD-A152 519

Application of artificial intelligence (AI) to radar image understanding

Deborah T. Franks
Joyce A. Musselman
John W. Sapp

Software Architecture & Engineering, Inc.
1500 Wilson Boulevard, Suite 800
Arlington, Virginia 22209

February 1985

Prepared for

U.S. ARMY CORPS OF ENGINEERS
ENGINEER TOPOGRAPHIC LABORATORIES
FORT BELVOIR, VIRGINIA 22060-5546

OFFICE OF NAVAL RESEARCH
800 NORTH QUINCY STREET
ARLINGTON, VIRGINIA 22217

APPROVED FOR PUBLIC RELEASE. DISTRIBUTION IS UNLIMITED.

E T L

Unclassified

REPRODUCED AT GOVERNMENT EXPENSE

SECURITY CLASSIFICATION OF THIS PAGE

REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION: Unclassified	1b. RESTRICTIVE MARKINGS
2a. SECURITY CLASSIFICATION AUTHORITY	3. DISTRIBUTION/AVAILABILITY OF REPORT: Approved for public release; distribution is unlimited
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE	
4. PERFORMING ORGANIZATION REPORT NUMBER(S): SAE-DC-85-R-004	5. MONITORING ORGANIZATION REPORT NUMBER(S): ETL-0387
6a. NAME OF PERFORMING ORGANIZATION: Software A&E, Inc. / 6b. OFFICE SYMBOL (If applicable)	7a. NAME OF MONITORING ORGANIZATION: Office of Naval Research
6c. ADDRESS (City, State and ZIP Code): 1500 Wilson Blvd., Suite 800, Arlington, VA 22209	7b. ADDRESS (City, State and ZIP Code): 800 N. Quincy Street, Arlington, VA 22217
8a. NAME OF FUNDING/SPONSORING ORGANIZATION: U.S. Army Engineer Topographic Laboratories / 8b. OFFICE SYMBOL (If applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER: N00014-84-C-0463
8c. ADDRESS (City, State and ZIP Code): Fort Belvoir, VA 22060-5546	10. SOURCE OF FUNDING NOS.: PROGRAM ELEMENT NO. / PROJECT NO. / TASK NO. / WORK UNIT NO.
11. TITLE (Include Security Classification): Application of Artificial Intelligence to Radar Image Understanding.	

12. PERSONAL AUTHOR(S): D.T. Franks, J.A. Musselman, J.W. Sapp

13a. TYPE OF REPORT	13b. TIME COVERED	14. DATE OF REPORT (Yr., Mo., Day)	15. PAGE COUNT
Final	FROM 1 Apr 84 TO 31 Dec84	85/02/28	42

16. SUPPLEMENTARY NOTATION

17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
FIELD	GROUP	SUB. GR.	Radar Image Understanding, Image Processing, Artificial Intelligence

19. ABSTRACT (Continue on reverse if necessary and identify by block number)

This report describes applied research into the application of artificial intelligence (AI) techniques to the problems associated with the extraction of terrain features from synthetic aperature radar (SAR) images. Specific AI techniques have been implemented and analyzed. They have given positive results. A conceptual model for an image-understanding system is described. The model provides the framework for a flexible experimental image-understanding research tool as well as potential for growth to an operational system.

ORIGINATOR - SUPPLIED KEY WORDS INCLUDE:

20. DISTRIBUTION/AVAILABILITY OF ABSTRACT: UNCLASSIFIED/UNLIMITED ☒ SAME AS RPT. ☐ DTIC USERS ☐	21. ABSTRACT SECURITY CLASSIFICATION: Unclassified
22a. NAME OF RESPONSIBLE INDIVIDUAL	22b. TELEPHONE NUMBER (Include Area Code) / 22c. OFFICE SYMBOL

DD FORM 1473, 83 APR EDITION OF 1 JAN 73 IS OBSOLETE.

SECURITY CLASSIFICATION OF THIS PAGE

ETL-0387
SAE-DC-85-R-004
February 1985

SUMMARY

The U.S. Army Engineer Topographic Laboratories contracted with Software A&E, Inc. to assist in conducting applied research in terrain feature extraction from synthetic aperture radar (SAR) images. The purpose of the research, carried out in 1984, was to evaluate the efficacy of artificial intelligence (AI) techniques in the classification of ambiguous areas in SAR images.

Heuristics and standard image processing techniques were incorporated into a knowledge-based expert system which was then applied to the SAR images. Results of the application of these techniques were compared to the results from traditional image processing techniques. Results of these experiments showed that artificial intelligence techniques hold significant promise for improving the understanding of ambiguous areas in SAR images.

The success of the image understanding experiments led to the formulation of a conceptual model of a system that could be used as a test bed for image understanding research. The conceptual model relies on techniques from the world of artificial intelligence as well as traditional image processing. The system architecture is sufficiently flexible to allow growth into an operational system capable of supporting tactical and strategic intelligence applications.

PREFACE

The work described in this report was undertaken as part of a series of projects performed by Software A&E in the application of artificial intelligence methods to problems faced by the U.S. Army Engineer Topographic Laboratories (ETL). The authors would like to acknowledge the contributions of Dr. P.F. Chen, Mr. Richard Hevenor and Mr. Neil Fox of ETL. Dr. Peter Lemkin provided invaluable insights and advice on image processing techniques.

1. INTRODUCTION

The U.S. Army Engineer Topographic Laboratories (ETL) have been conducting applied research in the area of terrain feature extraction from SAR images. The work has focused on human analysis of terrain features and the experimental application of image processing algorithms to that analysis. Even though the experimental results have been encouraging, it was felt that heuristic reasoning from the realm of artificial intelligence used in a complementary manner with the image processing algorithms could result in more powerful SAR image-understanding automated systems. Therefore, ETL contracted with Software A&E to analyze existing algorithms to determine how AI techniques could be employed to address problem areas and to perform experiments illustrating the application of AI to the image-understanding problem.

The statement of work specified four tasks:

Task 1 Study of Algorithms and Heuristics
Task 2 Develop a Skeletal Conceptual Model
Task 3 Heuristics Integration Experiment
Task 4 Experiment Evaluation

This final report describes the tasks carried out by Software A&E knowledge engineers in support of ETL objectives, the results achieved, and recommendations for further development of systems for research into image understanding.

2. TASK DEFINITIONS

The original tasks specified for the project were modified by the principal investigator with the concurrence of Software A&E to more accurately reflect the interests of the ETL researchers. The tasks actually carried out during the course of the project are described below.

2.1 Task 1: Study of Algorithms and Heuristics

In order to accomplish this task, the incorporation of existing image-understanding software from ETL with the Software A&E Knowledge Engineering System (KES) was necessary. This led to the transportation of ETL's software from the ETL HP1000 to Software A&E's VAX 11/750. Since the source code was written in a standardized version of FORTRAN it was theoretically capable of being ported to another system. The first task was accomplished after the porting of the ETL image understanding software to the VAX 11/750.

2.2 Task 2: Develop a Skeletal Conceptual Model

A conceptual model for a radar image-understanding system embodying standard image processing techniques and AI heuristic techniques was outlined. It generalized the findings of task 3. The skeletal model was documented in a technical memorandum that is attached as Appendix B of this report.

2.3 Task 3: Heuristics Integration Experiment

In this task the development of the original Radar Image Classification Aid (RICA) was initiated. Necessary heuristics and other AI techniques were integrated into the RICA together with the original image-understanding software from ETL. Experiments were performed using SAR imagery supplied by ETL as input for the RICA. A skeletal conceptual model was developed in Task 2 to generalize the original RICA. Development of the techniques in the context of the new RICA architecture was completed but experimental design and execution was not possible due to the funding limitation. Information gathered during the software development phase of the contract showed that the techniques implemented hold promise for significant improvements in the classificaiton of SAR images.

2.4 Task 4: Experiment Evaluation

The developments in Task 3 were evaluated and conclusions were made regarding the value of continuing the research begun in this exploratory study. The conclusions are documented in this final report of the project.

3. RADAR IMAGE CLASSIFICATION AID (RICA)

The Radar Image Classification Aid is an application of Artificial Intelligence techniques to the area of image processing. ETL currently uses a Bayes Classifier Program to identify 32 x 32 pixel areas called windows in a 512 x 512 pixel SAR image. This program classifies each window as one of the following feature classes: field, water, forest, or city. The result of this program is a 16 x 16 Feature Matrix that contains the classification of each window in the SAR image.

Problems arose when a window contained a border between two or more feature classes. As a partial solution to this problem ETL added a new feature class, border type, to the Bayes Classifier Program. This feature class was given to any window containing a border. The aim of RICA is to determine the feature classes that compose each of these border type windows.

3.1 AI Metholedogies

RICA incorporated three applications of artificial intelligence to the understanding of SAR images

- heuristic border search
- q-NN classification rule
- frame based reclassification

Each of these metholodogies are described in the following paragraphs.

3.1.1 Heuristic Border Search

The heuristic border search technique locates and arranges all of the border type windows in the Feature Matrix that will be reclassified by the Reclassification System Module (see description of software modules in appendix A).

The heuristic assumes that it is easier to reclassify those windows that have the most known about their neighborhoods and harder to reclassify windows with many unknowns in their neighborhoods. Note that if the method is provided the ability to learn by updating the Feature Matrix each time a border type window has been reclassified then those border type windows that originally had many unknowns in their neighborhoods will have been updated enough to reclassify them on subsequent iterations (see paragraph 5.1.4).

The ordered border information is provided to the Frame Based Reclassification System for use in its consideration of possible border reclassifications.

3.1.2 q-NN Classification Rule

The q-NN Classification Rule method examines the immediate neighborhood of a given border type window and calculates the percentage that each of the five feature classes composes in that neighborhood. The heuristic incorporated with the q-NN Classification Rule is, "the feature class with the highest percentage will have a higher liklihood of composing part of the border type window". The information is made available to the Frame Based Reclassification System for use in deciding the make-up of a border window.

3.1.3 Frame Based Reclassification

The Frame Based Reclassification method uses the information provided by the q-NN classification rule and other traditional image processing techniques to decide what combination of these feature classes best fits the information received about the window being reclassified.

The decision-making technique is based on minimal set cover theory. The Knowledge Engineering System (KES), a knowledge-based expert system building tool available from Software Architecture and Engineering, Inc., provides the Hypothesize and Test (HT) inferencing technique that has been used to implement frame based reclassification.

3.2 Results

The Radar Image Classification Aid correctly reclassified approximately 90% of the border type windows. Appendix A contains the technical memorandum that describes the RICA task. It details the software created for the experiment along with the results of the investigation made with RICA.

4. CONCEPTUAL MODEL

The RICA system was derived from the idea of a conceptual model for an image-understanding system. The conceptual model is intended for the image understanding researcher and, ultimately, for tactical and strategic intelligence personnel. The model combines standard image processing and artificial intelligence techniques in a single system whose architecture consists of a hierarchy of expert systems.

The system architecture described in the conceptual model is extremely flexible. It allows for the convenient introduction of new techniques as they are conceived. An mportant aspect of the model is its intelligent front end. The intelligent front end provides the user with the flexibility either to choose the way techniques are combined or to allow the system to determine the 'best' combination of image processing and AI techniques to apply to the task of understanding a SAR image.

The architecture of the model is described in detail in Appendix B.

5. FURTHER DEVELOPMENT OF RICA

The third task was concerned with the development and evaluation of techniques that might improve the classification of SAR images. Specifically, four enhancements were developed within the context of the RICA system. These enhancements are described below. See Appendix B for a full discussion of the part that these enhancements play in the conceptual model.

5.1 Enhancements

5.1.1 System Control. The system control expert system is intended to be a sophisticated intelligent front end for an image understanding system. Among other features of the modelled version, the front end would support the choice of image processing and AI techniques to be used in the task of understanding a SAR image. The fully implemented version is intended to make these choices with or without human intervention, relying on information in its own knowledge base(s).

For purposes of the third task, a simpler version of the system control expert system was implemented. This version provides the experimenter with the ability to manually specify the combination of techniques to be used in analyzing a SAR image.

5.1.2 Analysis of Window Quadrants. This enhancement enlarges upon the pixel level information available for image reasoning. The technique divides a border type window into quadrants. The area surrounding each quadrant is then analyzed to determine the most reasonable classification for that portion of the border window. Thus, each border window quadrant is analyzed in the context of its surrounding neighborhood.

5.1.3 Neighborhood Expansion. This enhancement provides a larger neighborhood to the q-NN Classification Rule module when the initial 3x3 neighborhood provides insufficient information for reasonable classification. This technique expands the neighborhood in steps (5x5, 7x7, etc.) until sufficient information has been obtained.

5.1.4 Learning. When a border window has been reclassified, the learning enhancement immediately updates the Feature Matrix so that the information is available during the reclassification of neighboring windows.

5.2 Experience With Enhancements

The enhancements were designed, coded, and tested during the final stages of the contract. Several test runs were executed for purposes of demonstrating the correctness of the code and to do preliminary evaluation of the enhancements. The preliminary evaluations did indicate a definite improvement in classification performance that would warrant further investigation. Limitations on contract funding prevented a substantial number of experimental runs that would determine the relative efficiencies of the enhancements, both individually and in combination.

6. CONCLUSIONS

The image understanding project has been a fruitful line of research that has proven the utility of the application of artificial intelligence to image understanding problems. The artificial intelligence methodologies have significantly improved the interpretation and classification of information from SAR images.

The conceptual model of an image understanding system, consisting of a hierarchy of cooperating expert systems, has been shown to be practical using existing technology. The architecture of the open ended system exemplified by the model is sufficiently flexible to support further research and to provide a basis for a production system for operational intelligence applications.

7. RECOMMENDATIONS

The project has proven the practicality and utility of the application of artificial intelligence techniques in the task of classifying SAR images. The research begun with this project should be carried further. Three lines of research should be investigated.

First, a series of experiments should be devised and carried out to determine the efficacy of the various techniques already implemented in the RICA system. Information should be developed to show the performance of each technique, both alone and in various combinations with other techniques. The sensitivity of each technique and combination of techniques to variations in quality of SAR images should also be explored.

Second, the techniques pioneered in this project should be refined and extended. New techniques should be devised and tested for their practicality and utility.

Third, the system embodied in the conceptual model should be completed and studied. This system has important contributions to make in both the short and long terms. In the short term, the model provides a flexible and powerful test bed for new ideas in image understanding. In the long term, the model provides the basis for the economical development of an operational image understanding system of unparalleled capability. It is strongly recommended that a prototype of such an operational system be developed and evaluated.

ETL-0387
SAE-DC-85-R-004
February 1985

APPENDIX A

Radar Image Classification Aid (RICA) Experiment Evaluation

Experiment Evaluation
Analysis of the Results from RICA
Problem Statement 1

1. Introduction

The Radar Image Classification Aid (RICA) is an application of Artificial Intelligence (AI) techniques to the area of image processing. The U.S. Army Engineer Topographic Laboratories (ETL) currently uses a Bayes Classifier Program to identify 32 x 32 pixel areas called windows, in a 512 x 512 pixel SAR image. This program classifies each window as one of the following feature classes: field, water, forest, or city. The result of this program is a 16 x 16 Feature Matrix that contains the classification of each window in the SAR image. Problems arose when a window contained a border between two or more feature classes. Toward a solution of this problem ETL added a new feature class; border type or BDR, to the Bayes Classifier Program. This feature class was given to any window containing a border. The aim of RICA is to determine the feature classes that compose each of these border type windows.

2. Primary Applications of AI

There are three primary applications of AI in the current RICA system: Heuristic Border Search, q-NN Classification Rule, and a Frame Based Re-classification System. Each of these applications is represented by a module in the RICA system's module hierarchy as shown in the Appendix.

2.1 Heuristic Border Search

The purpose of the Heuristic Border Search Module is to locate and arrange all of the border type windows in the Feature Matrix that will be re-classified by the Re-classification System Module. The heuristic used to arrange the border type windows is that it would be easier to re-classify those windows that have the most known about their neighborhoods first, and harder to re-classify windows with many unknowns in their neighborhoods. This is done by examining the immediate neighborhood (a 3 x 3 matrix) and determining the number of unknown or border type windows that reside there. The idea behind this is that when RICA is given the capability to 'learn', updating the Feature Matrix each time a border type window has been re-classified, then eventually those border type windows that originally had many unknowns in their neighborhoods will have been updated enough to re-classify them.

2.2 q-NN Classification Rule

The q-NN Classification Rule Module is based on the "nearest neighbor" principle and q-NN classification rule [TOU74]. The difference is that the q-NN Classification Rule Module does not actually re-classify a border type window in the Feature Matrix. It merely examines the immediate neighborhood of a given border type window and calculates the percentage that each of the five feature classes composes in that neighborhood. The Frame Based Re-classification System will use the information gathered by the q-NN Classification Rule Module to make a decision about what feature classes make up the components of the border window.

2.3 Frame Based Re-classification System

The Frame Based Re-classification System is written in the Software Architecture and Engineering's (SAE) Knowledge Engineering System (KES), Hypothesize and Test (HT) subsystem language [KES84]. This RICA module does the actual re-classification of the border type windows. It gathers information about a given border type window and its surrounding neighborhood from other RICA modules. That information is then used with the frame based descriptions of each of the five feature classes (field, water, forest, city, and border) to decide what combination of these feature classes best fits the information received about the window being re-classified. The concept behind the KES HT subsystem is based on minimal set cover theory [REG83].

3. Results

The Initial Classification Module is the Bayes Classifier Program from ETL. It provides the initial Feature Matrix upon which the remainder of the RICA system is based. The following is a discussion of the results of applying the AI applications to the task of determining the components of each previously defined border type window. (The percentages used in this report are the averages between the results of the images UNF014 and UNF026, shown at the end of this Appendix.)

3.1 Initial Feature Matrix Classification

In transferring the Initial Classification software from the ETL HP 1000 to Software A&E's VAX 11/750, differences occurred between the classification of the SAR image obtained at each installation. In the testing of RICA, 94.5 percent of the windows were classified with the same feature classes at Software A&E and ETL. Of the 5.5 percent that were classified differently, approximately 2.2 percent were more accurate than the classifications obtained at ETL when the actual SAR image was viewed. The remaining 3.3 percent were not classified more accurately.

The causes of the differences in the initial classifications have not been completely determined, but it is thought that they were caused by differences in the inverted mean and covariance matrices and/or the differences in the precision in the different computer systems that were used.

Although these differences may have had a slight impact on the final re-classification of the border type windows, the integrity of the RICA system was not affected since the purpose of this project was to determine whether AI techniques could aid in image understanding and not actual image processing.

3.2 Feature Matrix Re-Classification

The Feature Matrix was composed of approximately 11 percent border type windows. Of those windows, RICA re-classified 89.5 percent with a total or partially correct feature class value. The results from RICA were compared against values that were determined beforehand by studying the actual SAR image.

Out of the 89.5 percent, 60.5 percent of the border type windows were re-classified with 100 percent correct feature classes. This means that the feature classes that RICA selected were complete and accurate.

By definition, a border type window should be composed of two or more feature classes, but in 16.5 percent of the border type windows RICA was only able to identify one of these feature classes. In all of these cases, the feature class selected was one of the correct classes, and also was the class that comprised the majority of the area in the window.

The reason that RICA was only able to identify one of the border type window's feature classes was due to the fact that there was not enough information available in the neighborhood to make a reasonable selection. A 3 x 3 neighborhood was used to help determine the value of the border type window. In the case of these 16.5 percent, approximately 70 percent of the neighborhood was comprised of the feature class that RICA selected. The remaining 30 percent was divided evenly among one or more of the other feature classes without a strong enough certainty on any one of them to make an assertion as to which one(s) made up up the remaining portion of the window.

The remaining 12.5 percent of the correctly re-classified border type windows were also only partially re-classified, but these windows contained an 'unknown' class in its new value. In

this case, as in the previous case, those feature classes that were selected along with the 'unknown' value were correct, but the re-classification value was incomplete. This occurred when 40 percent or more of a window's neighborhood consisted of other border type or 'unknown' windows.

The remaining 10.5 percent of the total border type windows were re-classified incorrectly. In all cases, one of the feature classes selected by RICA was correct and the remaining value(s) were incorrect. With the information available, RICA made a 'reasonable' re-classification decision and had more information been available (such as the direction that the border runs), RICA could have been able to make more accurate decisions.

4. Analysis

In general, RICA was successful in its re-classification of the border type windows in the Feature Matrix. With the limited amount of information that was available to RICA, it was able to re-classify to some degree of correctness approximately 90 percent of the border type windows. By adding the proposed enhancements of a learning capability and neighborhood expansion, and by adding the additional information of various image feature data, the re-classification done by RICA should become more complete and more accurate.

REFERENCES

BALL82
Ballard, D. H. and C.M. Brown, Computer Vision, Prentice-Hall: Inglewood Cliffs,NJ, 1982.

BRAD82
Brady, M., Computational Approaches to Image Understanding, ACM Computing Surveys, March 1982, Vol. 14, Number 1, pp. 3-71.

FUKU72
Fukunaga, K., Introduction to Statistical Pattern Recognition, Academic Press: New York, 1972.

GLIC83
Glicksman, J., Using Multiple Information Sources in a Computational Vision System, Proc Int'l Joint Conference Artificial Intelligence, August 1983, pp. 1078-1080.

HAVE83
Havens, W. and A. Mackworth, Representing Knowledge of the Visual World, Computer, October 1983.

HORO78
Horowitz, E. and S. Sahni, Fundamentals of Computer Algorithms, Computer Science Press, Inc., 1978, pp. 121-127

KES84
Knowledge Engineering System, Knowledge Base Author's Manual, Software Architecture & Engineering, Inc., June 1984

KNUT73
Knuth, D. E., The Art of Computer Programming, Sorting and Searching, Volume 3, Addison-Wesley Publishing Company, Inc., 1973, pp. 114-123

MACK78
Mackworth, A. K., Vision Research Strategy: Black Magic, Metaphors, Miniworlds and Maps, Computer Vision Systems, 1978

MACK82
Mackworth, A. K. and E. C. Freuder, The Complexity of Some Polynomial Network Consistency Algorithms for Constraint Satisfaction Problems, Technical Report 82-6, August 1982

PEAR84
Pearl, J., Heuristics, Intelligent Search Strategies for Computer Problem Solving, Addison-Wesley Publishing Company, Inc., 1984

PERR78
Perry Cole, J. W., ANSI Fortran IV, A Structured Programming Approach, WM. C. Brown Company Publishers, 1978

PRAT78
Pratt, W. K., Digital Image Processing, John Wiley & Sons, 1978

REGG83
Reggia, J., D. Nau, and P. Wang, Diagnostic Expert Systems Based on a Set Covering Model, Int. J. Man-Machine Studies, Nov. 1983.

ROSE82
Rosenfeld, A. and A. C. Kak, Digital Picture Processing, Volume 2 Academic Press, 1982

SEED81
Seeds, H. L., Structuring Fortran 77 for Business and General Applications, John Wiley & Sons, 1981

TOU74
Tou, J. T. and R. C. Gonzalez, Pattern Recognition Principles, Addison-Wesley Publishing Company, Inc., 1974

WANG83
Wang,S., R.M. Haralick, and J. Campbell, Relative Elevation Determination from Landsat Imagery, Department of Computer Science, Electrical Engineering and Geopraphy, VPI & SU, 1983.

APPENDIX

The appendix is a photocopy of the RICA System presentation given to ETL staff members on 30 August 1984.

Radar Image Classification Aid

(RICA)

AN APPLICATION OF
ARTIFICIAL INTELLIGENCE
TO
IMAGE UNDERSTANDING

August 30, 1984

Software Architecture & Engineering, Inc.
1500 Wilson Boulevard, Suite 800
Arlington, VA 22209

PRIMARY APPLICATIONS OF AI

1. HEURISTIC BORDER SEARCH

   - locate all border windows
   - arrange border windows in order to be classified

2. Q-NN CLASSIFICATION RULE

   - count the number of each feature_class in neighborhood
     assign <h>, <m>, <l>
   - if 40% of neighborhood = BDR
     then part of classification = unknown

3. RECLASSIFICATION

   - frame-based knowledge representation -- KES HT
   - minimal set covers

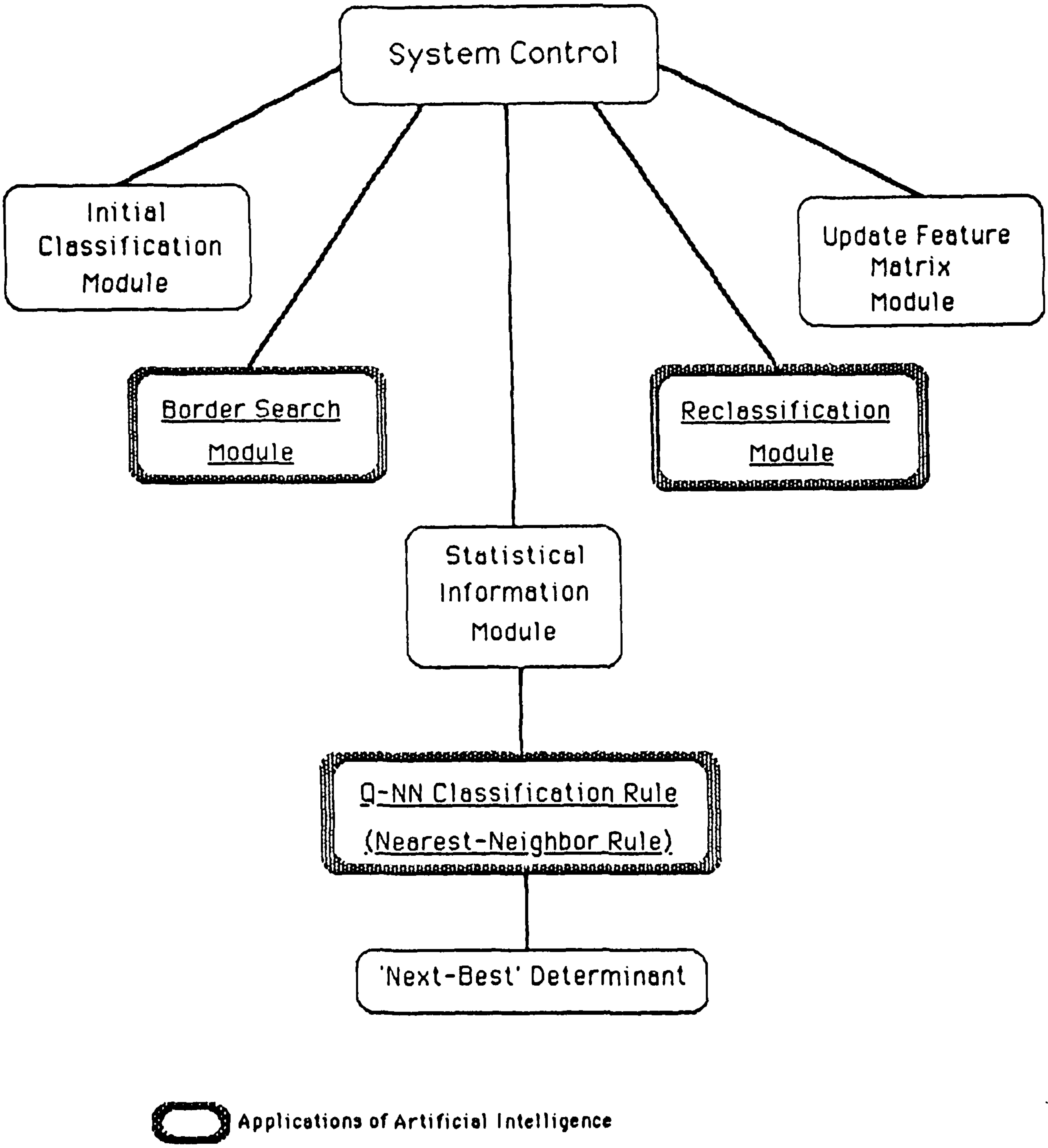
Analysis of Bayes Classifier

ETL -vs- SAE

Image UNF014	Number	Percentage
• Windows classified the same	242	94.5%
• Windows classified differently:		
• **Different from ETL but closer to actual**	8	3.1%
• **Different from ETL but not closer to actual**	6	2.4%
	====	======
	256	100.0%

Image UNF026		
• Windows classified the same	242	94.5%
• Windows classified differently:		
• **Different from ETL but closer to actual**	3	1.2%
• **Different from ETL but not closer to actual**	11	4.3%
	====	======
	256	100.0%

RICA Module Hierarchy



Based on the information supplied by the Initial Classification Module, the following is an analysis of the Re-Classification done by RICA.

<u>Image UNF014</u>

Total BDR type windows	23	9.0%
100% Correct Classification		65.0%
* Only Partial Classification Determined		17.0%
* With *unknown* as Part of New Classification		9.0%
		======
<u>Total Correct</u>		91.0%
Incorrect Classifications		9.0%

<u>Image UNF026</u>

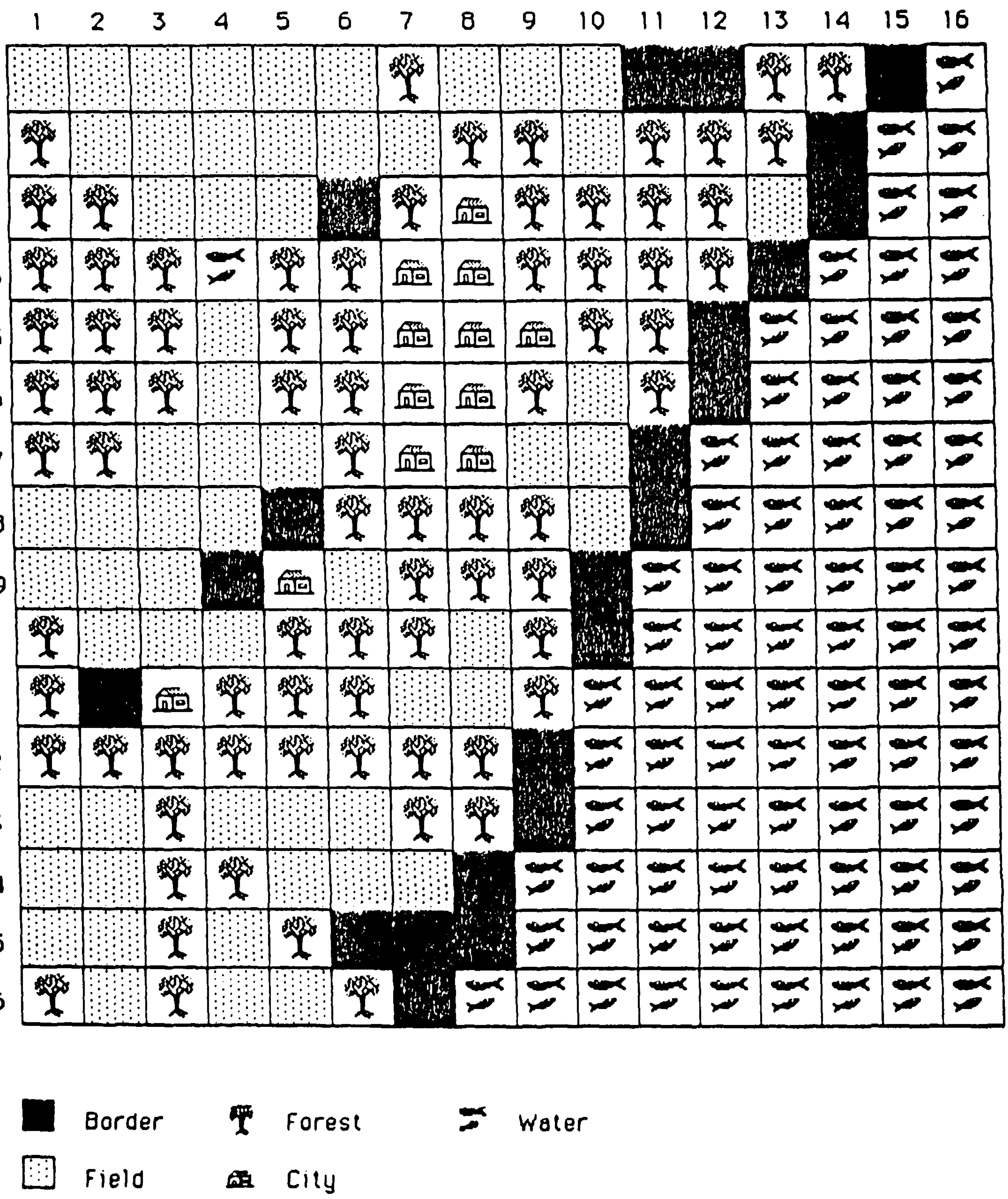
Total BDR type Windows	32	12.5%
100% Correct Classification		56.0%
* Only Partial Classification Determined		16.0%
* With *unknown* as Part of the New Classification		16.0%
		======
<u>Total Correct</u>		88.0%
Incorrect Classifications		12.0%

* Classifications will be affected by RICA enhancements

FEATURE MATRIX OF UNF014

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	fld	fld	fld	fld	fld	fld	fst	fld	fld	fld	BDR	BDR	fst	fst	BDR	wat
2	fst	fld	fld	fld	fld	fld	fld	fst	fst	fld	fst	fst	fst	BDR	wat	wat
3	fst	fst	fld	fld	fld	BDR	fst	cty	fst	fst	fst	fst	fld	BDR	wat	wat
4	fst	fst	fst	wat	fst	fst	cty	cty	fst	fst	fst	fst	BDR	wat	wat	wat
5	fst	fst	fst	fld	fst	fst	cty	cty	cty	fst	fst	BDR	wat	wat	wat	wat
6	fst	fst	fst	fld	fst	fst	cty	cty	fst	fld	fst	BDR	wat	wat	wat	wat
7	fst	fst	fld	fld	fld	fst	cty	cty	fld	fld	BDR	wat	wat	wat	wat	wat
8	fld	fld	fld	fld	BDR	fst	fst	fst	fst	fld	BDR	wat	wat	wat	wat	wat
9	fld	fld	fld	BDR	cty	fld	fst	fst	fst	BDR	wat	wat	wat	wat	wat	wat
10	fst	fld	fld	fld	fst	fst	fst	fld	fst	BDR	wat	wat	wat	wat	wat	wat
11	fst	BDR	cty	fst	fst	fst	fld	fld	fst	wat	wat	wat	wat	wat	wat	wat
12	fst	fst	fst	fst	fst	fst	fst	fst	BDR	wat	wat	wat	wat	wat	wat	wat
13	fld	fld	fst	fld	fld	fld	fst	fst	BDR	wat	wat	wat	wat	wat	wat	wat
14	fld	fld	fst	fst	fld	fld	fld	BDR	wat	wat	wat	wat	wat	wat	wat	wat
15	fld	fld	fst	fld	fst	BDR	BDR	BDR	wat	wat	wat	wat	wat	wat	wat	wat
16	fst	fld	fst	fld	fld	fst	BDR	wat	wat	wat	wat	wat	wat	wat	wat	wat

FEATURE MATRIX OF UNF014



RECLASSIFICATIONS OF BORDER-TYPE WINDOWS IN UNF014

Window at location (11,2):	field forest	Window at location (2,14):	water forest
Window at location (3,6):	field forest	Window at location (7,11):	water field
Window at location (9,4):	field	Window at location (6,12):	water forest
Window at location (10,10):	water forest	Window at location (5,12):	water forest
Window at location (8,5):	field forest	Window at location (15,8):	water
Window at location (12,9):	water forest	Window at location (14,8):	water forest
Window at location (8,11):	water field	Window at location (15,7):	field unknown
Window at location (9,10):	water forest	Window at location (1,11):	field forest
Window at location (13,9):	water forest	Window at location (1,12):	forest
Window at location (15,6):	field forest	Window at location (1,15):	water forest
Window at location (3,14):	water	Window at location (16,7):	water forest unknown
Window at location (4,13):	water forest		

PLANNED ENHANCEMENTS

1. LEARNING

2. STRENGTH OF REGIONS IN BDR WINDOW NEIGHBORHOODS

3. PEAK ANALYSIS OF THE GRAY SCALE HISTOGRAM

ETL-0387
SAE-DC-85-R-004
February 1985

APPENDIX B

A Conceptual Model For An Image Understanding System

A CONCEPTUAL MODEL FOR AN IMAGE UNDERSTANDING SYSTEM

1. INTRODUCTION

The U.S. Army Engineer Topographic Laboratory has been conducting applied research in the area of terrain feature extraction from aerial radar images. The work has focused on human analysis and the experimental application of image processing algorithms. Even though the experimental results are encouraging, it is felt that heuristic reasoning from the realm of artificial intelligence (AI) used in a complementary manner with the image processing algorithms can result in more powerful radar image understanding automated systems. The ETL contracted with Software A&E, Inc., to analyze existing algorithms, to determine how AI techniques can be employed to address problem areas, and to perform experiments that illustrate the application of artificial intelligence to the image understanding application.

As part of that contract, Software A&E was tasked to develop and outline a conceptual model for a radar image understanding system that would embody both standard image processing techniques and AI techniques. This technical memorandum documents the required conceptual model.

The model described in this memorandum derives from the programs known as the Radar Image Classification Aid, or RICA, developed for the task in the Statement of Work entitled "Study of Algorithms and Heuristics." The second section of this memorandum describes a conceptual model for an image understanding system and then proceeds to outline the Radar Image Classification Aid thus showing the feasibility of the conceptual model.

The system described by this model is aimed initially at the image understanding researcher. It provides a flexible framework into which new techniques, both AI and non-AI, can be easily integrated, used in a variety of combinations, and evaluated. That same flexibility and the use of an intelligent front-end will also benefit the operational user because it will be capable of applying the best available techniques and combinations of techniques to the solution of a variety of image understanding problems.

2. The Model

This section is twofold in purpose. First a conceptual model for an image understanding system is outlined. Then following in line with the conceptual model the experimental image understanding system (RICA) which was developed is presented.

2.1 The Conceptual Model

The conceptual model for an image understanding system embodies both standard image processing and AI techniques. The model is designed with a flexible framework allowing the image understanding researcher to incorporate new AI and image processing techniques into the system. This framework also allows the efficient evaluation of the results of new techniques, alone or in combination with other techniques by permitting the user or the intelligent front-end to select the techniques used.

The architecture of the Conceptual Model consists of three levels (see figure 2.1-1). At the top, an intelligent front-end called the System Control Expert System governs the processing of a radar image. The purpose of this expert system is to determine the 'best' combination of image processing and AI techniques to apply to the task of understanding a radar image. This expert system would continually interpret results received from the various sub-processes and adjust subsequent processing to account for interim results. In order to keep the model as flexible as possible the user would also have the ability to request control over the selection of the combination of techniques to be used.

Below the System Control Expert System are two modules: the Information Gathering Module, and the Image Reasoner Module. The purpose of the Information Gathering Module is to furnish detailed information about the image to the system. Two types of information can be supplied: Image Processing Information and Contextual Image Information.

Image Processing Information consists of results from standard image processing techniques such as Bayes Theorem, Histogram analysis, Hough Transform, etc., which are generally applied to an entire image. Contextual Image Information consists of algorithms enhanced with heuristics that are typically applied to a specific area or region in a radar image but that could be applied to an entire image.

The purpose of the Image Reasoner Module is to provide the ability to 'reason' or make decisions about some aspect of radar image understanding. This module consists of a series of domain specific expert systems. When needed these expert systems would use results from the Information Gathering Modules to aid in the

'reasoning' process. For example, in the RICA, an Image Reclassification Expert System has the ability to determine the components of windows (32 x 32 pixel areas) that are made up of at least two of the following feature classes: field, forest, water, city. There could also be expert systems that contain knowledge in domains such as classifying an entire image for a specific geographic location, checking the feasibility of a classification or classifications in a given image or image type, etc.

CONCEPTUAL MODEL ARCHITECTURE

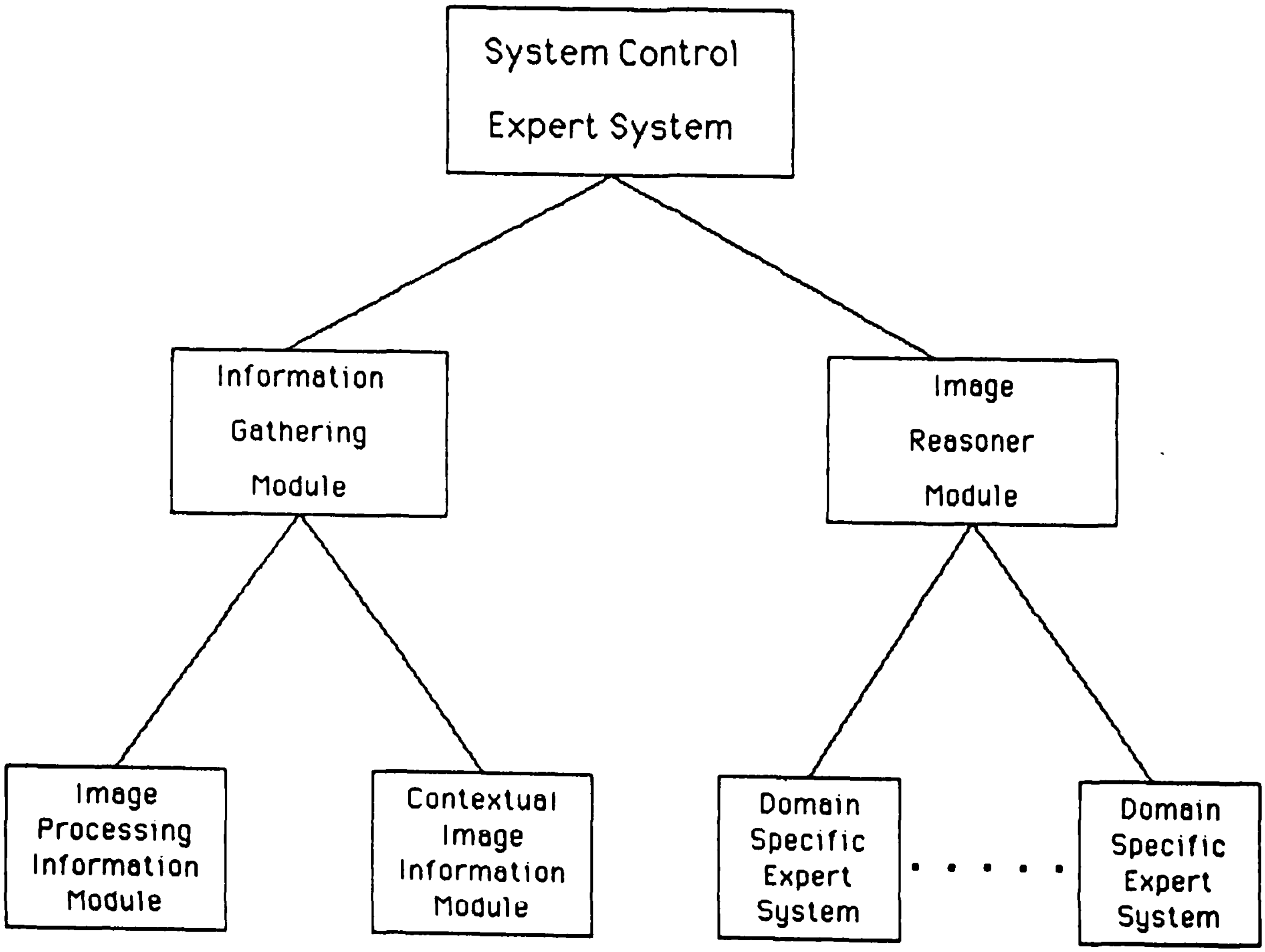


Figure 2.1-1

2.2 Radar Image Classification Aid (RICA)

RICA is an application of AI techniques to the area of image understanding. RICA divides a 512x512 pixel radar image in to 32x32 pixel areas called windows. Depending on its contents each window is classified as one of the following feature classes: field, forest, water, city, or border. A border window represents an area consisting of at least two of the remaining four feature classes. The aim of RICA is to determine the feature classes that compose each of the border type windows in a given radar image. In general RICA reclassified each border type window, one at a time, by requesting various types of information about the window and its surrounding area, and then reasoning about that information.

2.2.1 The Architecture of RICA

The RICA architecture consists of several levels, with each level representing varying degrees of information and detail (see figure 2.2.1-1). At the top level of the RICA architecture is the System Control Expert System (1.0). This module provides the RICA user with the ability to tell the system the various types of preliminary processing to be performed on an image prior to reclassification and to specify which of the available processing options should be used. The System Control Expert System provides a basis for further enhancements in which a RICA user may let the System Control Expert System 'decide' the best means of processing an image.

Below the System Control Expert System are two modules: the Information Gathering Module (1.1) and the Image Reasoner Module (1.2). The purpose of the Information Gathering Module is to provide the System Control Expert System with various types of image information. This module consists of two modules: the Image Processing Information Module (1.1.1) and the Contextual Image Information Module (1.1.2).

The purpose of the Image Processing Information Module is to provide standard image processing types of algorithms which are generally applied to an entire radar image. This module currently consists of the Initial Classification Module (1.1.1.1) which is based on the Bayes Classifier program used at the ETL. The Initial Classificaton Module performs the task of initially assigning one of the feature classes (field, forest, water, city, border) to each window in a given image. The result of this module is a 16x16 Feature Matrix that contains the initial classification of each window in the radar image. The Feature Matrix may then be used by other modules in the system.

The Contextual Image Information Module (1.1.2) provides the system with algorithms enhanced with heuristics. These algorithms are typically applied to specific regions in a radar image but can be applied to an entire image. This module currently consists of three modules: the Border Search Module (1.1.2.1), the Pixel Level Information Module (1.1.2.2), and the Feature Matrix Level Information Module (1.1.2.3).

The Border Search Module is used by the RICA to locate and arrange all border type windows in the order in which they are to be reclassified. The heuristic used in this module is that border type windows with the most known, meaning the least number of unknown or border type windows in their neighborhood (a 3 x 3 matrix) are candidates to be reclassified first. Also, if the RICA used its ability to 'learn' as it goes through the reclassification process, then eventually those border type windows that originally had many unknowns in their neighborhoods will have been updated enough to reasonably reclassify them.

The Pixel Level Information Module provides pixel level contextual information to the RICA system. The difference between the function of this module and the Image Processing Module (1.1.1) is that this module does image processing on a selected area of the image (a window for instance) and the Image Processing Module works with an entire image. This module currently consists of two modules: the 'Next Best' Determinant Module (1.1.2.2.1), and the Analysis of Window Quadrants Module (1.1.2.2.2).

The 'Next Best' Determinant Module finds the next best legal feature class for a window. By definition, the best feature class would be the current feature class. This classification would also correspond to the highest determinant. Therefore, the 'Next Best' legal determinant would describe a feature class that has the next highest determinant value and is also present in the window's neighborhood.

The Analysis of Window Quadrants Module divides a border type window into quadrants. The area surrounding each quadrant is then analyzed to determine the most reasonable classification for that portion of the border window. Therefore each border window quadrant is analyzed in the context of its surrounding neighborhood.

The Feature Matrix Level Information Module (1.1.2.3) provides abstract Feature Matrix level contextual information to the RICA, using AI and image processing techniques.

This module currently consists of two modules: the q-NN Classification Rule Module (1.1.2.3.1), and the Neighborhood Expansion Module (1.1.2.3.2). These two modules actually work

together. The q-NN Classification Rule Module examines the 3x3 neighborhood of a given border type window and calculates the percentage that each of the five possible feature classes composes in that neighborhood. This module uses the heuristic that the feature class with the highest percentage will have a higher likelihood of composing part of the border type window.

If there is not 'sufficient information' found in the initial 3x3 neighborhood, and if the Neighborhood Expansion Module has been activated by the System Control Expert System (currently this must be indicated by the user), then the size of the neighborhood will be expanded until a reasonable amount of information has been obtained. In this case, 'sufficient information' means that less than 50% of a neighborhood are border type windows. With each expansion iteration the q-NN Classification Rule Module is used.

The second module under the System Control Expert System is the Image Reasoner Module (1.2). The task of this module is to provide the facility to 'reason' about different aspects of a radar image using various domain specific expert systems. In the current RICA system there is only one domain specific expert system: the Image Reclassification Expert System (1.2.1), although it could be expanded to contain any number of expert systems.

The domain of the Image Reclassification Expert System is the reclassification of border type windows in a Feature Matrix. It does this through the use of other modules and sub-expert systems. The current implementation contains a Reclassification Expert System (1.2.1.1), and a 'Learning' Module (1.2.1.2).

The Reclassification Expert System is a framed based system written in the Software A&E Knowledge Engineering System (KES), Hypothesize and Test (HT) subsystem language [KES84], [REGG83]. Its purpose is to gather information about a given border type window, provided by the various modules under the Information Gathering Module (1.1), and determine the feature classes that compose that window. It does not do the actual reclassification however, but simply makes a decision as to what combination of the four possible feature classes best fits the framed based descriptions for each of the feature classes.

The 'Learning' Module takes the Reclassification Expert System's decision and updates the Feature Matrix, making that new information available when neighboring windows are reclassified.

RICA Architecture

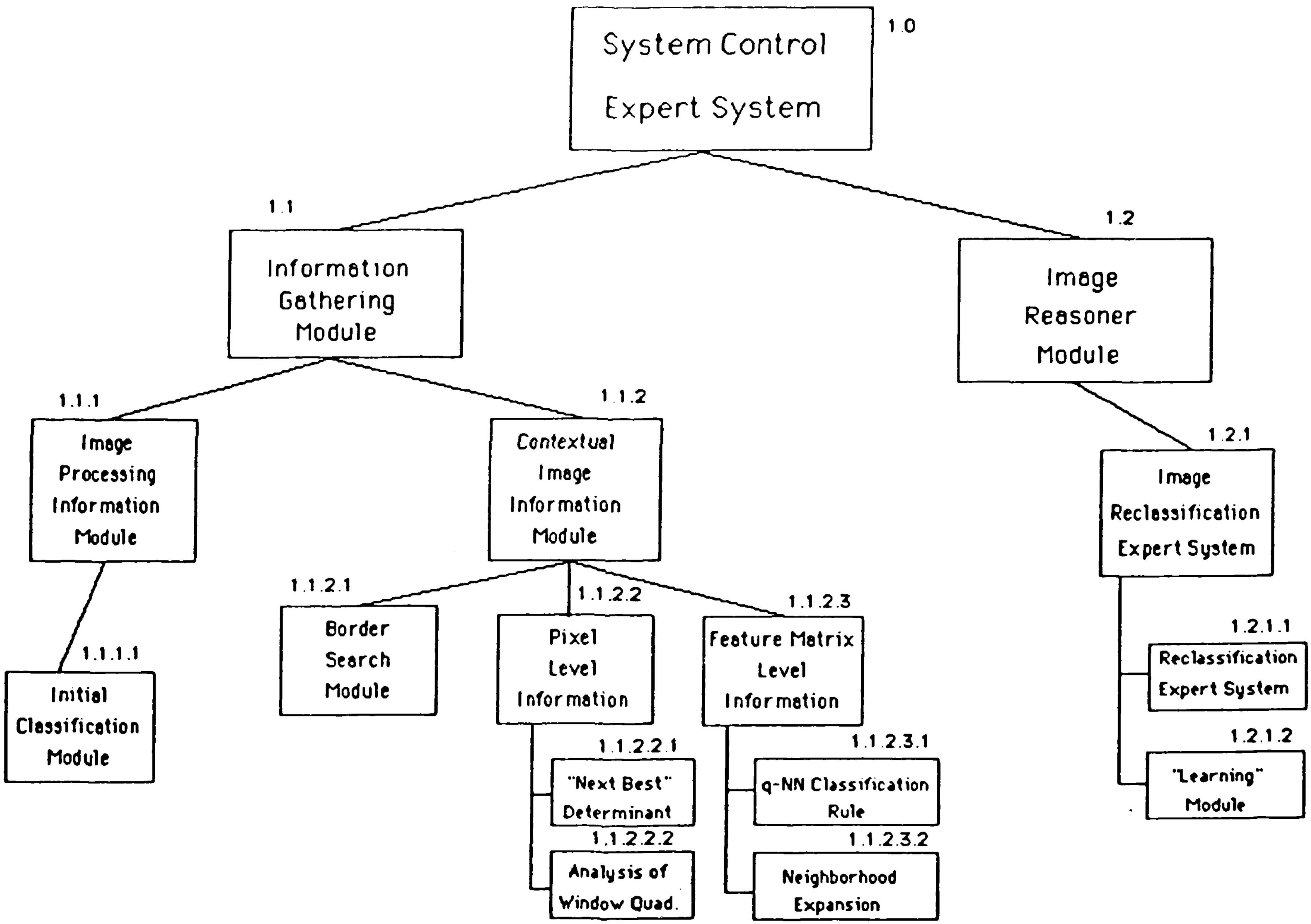


Figure 2.2.1-1

3. Conclusion

This technical memorandum has described a conceptual model for an image understanding system. The model provides an intelligent front-end that can interpret results of ongoing processing and adjust subsequent processing to account for those interim results. The architecture of the model is such that new techniques can be easily added and evaluated. The model features an embedded inference mechanism that allows the integration and evaluation of heuristic techniques based upon knowledge based expert system technology into the image understanding system.

Research and development into new and enhanced image understanding techniques can be advanced with the creation and use of increasingly powerful tools. The system described in this memorandum is one such tool, a test bed where new techniques can be prototyped and easily integrated with other techniques, that can provide researchers with the capability to efficiently evaluate new techniques alone and in various combinations with other techniques. Such a system could indeed, naturally evolve into a system useful in an operational environment.

REFERENCES

BALL82
Ballard, D. H. and C.M. Brown, Computer Vision, Prentice-Hall: Inglewood Cliffs,NJ, 1982.

BRAD82
Brady, M., Computational Approaches to Image Understanding, ACM Computing Surveys, March 1982, Vol. 14, Number 1, pp. 3-71.

FUKU72
Fukunaga, K., Introduction to Statistical Pattern Recognition, Academic Press: New York, 1972.

GLIC83
Glicksman, J., Using Multiple Information Sources in a Computational Vision System, Proc Int'l Joint Conference Artificial Intelligence, August 1983, pp. 1078-1080.

HAVE83
Havens, W. and A. Mackworth, Representing Knowledge of the Visual World, Computer, October 1983.

HORO78
Horowitz, E. and S. Sahni, Fundamentals of Computer Algorithms, Computer Science Press, Inc., 1978, pp. 121-127

KES84
Knowledge Engineering System, Knowledge Base Author's Manual, Software Architecture & Engineering, Inc., June 1984

KNUT73
Knuth, D. E., The Art of Computer Programming, Sorting and Searching, Volume 3, Addison-Wesley Publishing Company, Inc., 1973, pp. 114-123

MACK78
Mackworth, A. K., Vision Research Strategy: Black Magic, Metaphors, Miniworlds and Maps, Computer Vision Systems, 1978

MACK82
Mackworth, A. K. and E. C. Freuder, The Complexity of Some Polynomial Network Consistency Algorithms for Constraint Satisfaction Problems, Technical Report 82-6, August 1982

PEAR84
Pearl, J., Heuristics, Intelligent Search Strategies for Computer Problem Solving, Addison-Wesley Publishing Company, Inc., 1984

PERR78
Perry Cole, J. W., ANSI Fortran IV, A Structured Programming Approach, WM. C. Brown Company Publishers, 1978

PRAT78
Pratt, W. K., Digital Image Processing, John Wiley & Sons, 1978

REGG83
Reggia, J., D. Nau, and P. Wang, Diagnostic Expert Systems Based on a Set Covering Model, Int. J. Man-Machine Studies, Nov. 1983.

ROSE82
Rosenfeld, A. and A. C. Kak, Digital Picture Processing, Volume 2 Academic Press, 1982

SEED81
Seeds, H. L., Structuring Fortran 77 for Business and General Applications, John Wiley & Sons, 1981

TOU74
Tou, J. T. and R. C. Gonzalez, Pattern Recognition Principles, Addison-Wesley Publishing Company, Inc., 1974

WANG83
Wang,S., R.M. Haralick, and J. Campbell, Relative Elevation Determination from Landsat Imagery, Department of Computer Science, Electrical Engineering and Geopraphy, VPI & SU, 1983.

END

FILMED

5-85

DTIC